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Fusion of Artificial Intelligence in Neuro-Rehabilitation Video Games

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ABSTRACT In this paper, an intuitive neuro-rehabilitation video game has been developed employing the fusion of artificial neural networks (ANNs), inverse kinematics (IK), and fuzzy logic (FL) algorithms. The embedded algorithms automatically adjust the game difficulty level based on the player's interaction with the game. Moreover, it is manifested as an alternative approach for possible movements to improve incorrect positioning through real-time visual feedback on the screen; 52 participants volunteered to engage in the program. Motor assessment scale (MAS) was determined to assess the participants' functional ability pre- and post-treatments. The system input is received via the Microsoft Kinect, a foot Pedal (Saitek), and the Thalmic Myo armband. The ANN classifier integrates the limb joints orientation, angular velocity, lower arms' muscle activity, hand gestures, feet sole (plantar) pressure parameters, and the MAS scores to learn from data and predict the improvement following the intervention. The fuzzy input generates a crisp output and provides a personalized rehabilitation program with the potential to be integrated into clinical protocols. Experiments to obtain the input signals and desired outputs were conducted for the learning and validation of the network. The networks pattern recognition, self-organizing map, and non-linear auto-regression analysis performed using feed-forward and Levenberg–Marquardt backpropagation (LMBP) procedure. The results showed the effectiveness of the non-linear auto-regression using the optimized LMBP algorithm to classify and visualize the target categories. Furthermore, the state of the network demonstrates the prediction accuracy exceeding 94%. Clustering algorithm grouped the data based on the similarity. Self-organizing map trained the network to learn the topology of samples with high correlation, presented outputs with high achievement.

INDEX TERMS Fuzzy logic, neuro-rehabilitation, pattern recognition, inverse kinematics, artificial neural network, classification.

I. INTRODUCTION

Multiple sclerosis (MS) is a common immune-system problem [1]. It is acknowledged that an unidentified environmental factor triggers the disease. Moreover, the progress and specific symptoms of the disease cannot be predicted in any one person [2]. According to [3], rehabilitation program could be advantageous to improve and keep up the functional capacity of patients in the face of disease progression. An expanding number of analysts focus on portraying the estimation of rehabilitation intercessions that can be utilized all through the disease, from the underlying side effects to the propelled stages [4]. Our previous research [5], [6] have also shown that integrating off-the-shelf devices with video game rehabilitation program could facilitate a platform to enable participants' sustainability, engagement, extended program duration, and increase the number of specific movements per session.

In this study, Artificial Neural Networks (ANNs) algorithms were employed to detect complex non-linear correlations among data collected from limbs. To develop an optimal classifier we integrated self-organizing map (SOM), non-linear autoregressive (NAR) and pattern-recognition with the two-layer feed-forward network. The NN clustering was utilized to train the algorithm based on inputs from devices and pattern generated through limb movement. The supervised NN was trained and validated based on independent data which is used to predict future events. Non-linear autoregressive neural network (NAR) approximation function was developed using Levenberg-Marquardt backpropagation (LMBP) learning rule to approximate the discrete non-linear autoregressive model. Integration of the reasonable

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Coordination of the reasonable fuzzy logic inference utilized an action which is progressively suitable for the player dependent on their performance additionally to stay away from any dissatisfaction or harm. Predefined fuzzy rules specified through the fuzzy presumption that affects the defuzzification and denormalization investment to the output. The upper-limb pattern recognition was performed using inputs from Microsoft Kinect, Myo armband, and Saitek foot Pedal. The hand gestures were separated into (reach, grab, release, idle). The body joints position, orientation, angular velocity, timing facilitated by Kinect. The pressures applied by feet sole on the foot Pedal were gathered and utilized for lower-limb pattern recognition and characterization. The foot Pedal additionally exchanged the players' feet action to the 3D world to control and move the avatar.

II. BACKGROUND

Numerous researchers have executed gait state organization [7]–[10]. For example, [8] used neural networks to analyze gait design in post-stroke subjects. They analyzed minimum and maximum angle conditions in lower-limb joints and compared that with the ANN to analyze the full improvement of lower-limb joint angle settings with 100% success rates. Reference [9] used a Bayesian regularization NN (BRNN), by executing regression analysis to determine a model planning the correlation within gait features and blood alcohol content. They revealed that a BRNN was an explicit method to identify the striking features of gait. Reference [10] created NN principles which can recognize the gait models. They applied Vicon Nexus to obtain the gait kinetic and kinematic parameters who suggested that NN rules have application in clinical settings. Reference [11] incorporated NN for the clarification of the indicative trial of pancreatic catalysts and decision making. Reference [12] used NNs to predict the post-operative gait pattern in Diplegic cerebral palsy patients who had two-sided rectus exchanges to the sartorius. They reasoned that the NN could be generalized and be a reliable indicator for prediction [13]. They reported that once NN prepared it is self-ruling, accommodative of any gait pattern and speed and time-saving. The upper-limb function is fundamental for a free-living since dysfunction from upper extremity impairs the performance of many daily activities such as dressing, bathing, and self-caring thus reducing functional independence [14]. To our knowledge, our investigation is the first to apply the ANN calculation to foresee/predict the upper limb patterns as well as classify the movement based on the data collected from subjects while sitting but engaging both upper and lower limbs during the exercise. It accommodates subjects who might suffer from maintaining the balance who could sit and play the game with no fear of falling.

III. MATERIALS AND METHODS

A. REHABILITATION VIDEO GAME

Fruit collection and manoeuvring in the park video game was developed in that the player controlled the avatar. The avatar moves inside the 3D world to collect fruits which are randomly spawned in different locations. Movement is managed by the foot pedal and required the player to reach the highlighted areas to collect virtual objects. As soon as the player reaches highlighted spots, a virtual basket appears which must is used to collect fruits. The player interacts with virtual fruits by showing the hand palm to the Kinect device followed by opening/closing fingers (spread fingers and fist gesture) to exercise the grabbing effect. After grabbing the player should continue holding it (fist gesture) and just release it if reached above the virtual basket (spread fingers gesture).

A substantial release condition hailed to the player by means of visual input, by exchanging blazing red spots to green. Once released, gravity pulls the fruit down, it lands in the basket, the score is accomplished, and the fruit vanishes [15]. The foot Pedal algorithm predicts the measure of force applied to footrests and concludes if the steps are taken in order unless the forward movement would not take place. The left/right feet force takes the avatar forward, and toe strains facilitate turning left or right. The footrest dimensions are adaptable with non-slip materials to secure the foot unfaltering. Left foot maximum pressure value is presented as -1, neutral is 0, and a right foot pressure is $+1$. If the normal is negative the left foot is predominant if it is positive the right foot is dominant, and zero means both feet apply equal pressures (best condition). A healthy movement manifested by wave oscillating symmetrically around zero ($mean = 0$). The collected data are body's joint orientation and angular velocity, hand gestures, fruits' spawn location, collection and release timing, lower arm's IMU and EMG data, foot Pedal data which are saved in the hard disk and utilized by NN algorithm.

B. OFF THE SHELF DEVICES

Microsoft Kinect V2 with skeleton following framework offers a compact 3D movement capture ability, empowering user to control and connect with a game in real-time. Kinect comprises of an infrared laser and a (Red-Green-Blue) camera. It can recognize the position and orientation of body joints, angular velocity, and gestures. Fig. 1 (a), indicates anatomical plane, sagittal and frontal plane, shoulder's abduction-adduction, flexion-extension, wrist pronation-supination, and flexion-extension of hand. The joint progressive system is delineated in Fig. 1 (b). The units have their root in the Spine and spread out downwards to the focal point of the hip points to the right and left hip. The SP stretches out upwards to the center of the shoulders and head, shoulder, elbow, wrist, and hand.

Thalmic Myo armband has an accelerometer, gyroscope, magnetometer (inertial measurement unit (IMU)) and eight electroMyography (8-EMG) sensors. The nine-axis IMU records position and orientation of a lower arm in real-time. An acceleration represents the acceleration the arm undergoes at any given time in three-dimension (left/right, up/down and forward/backwards). Through the force-detection mechanism, it captures the force created by the accelerometer in

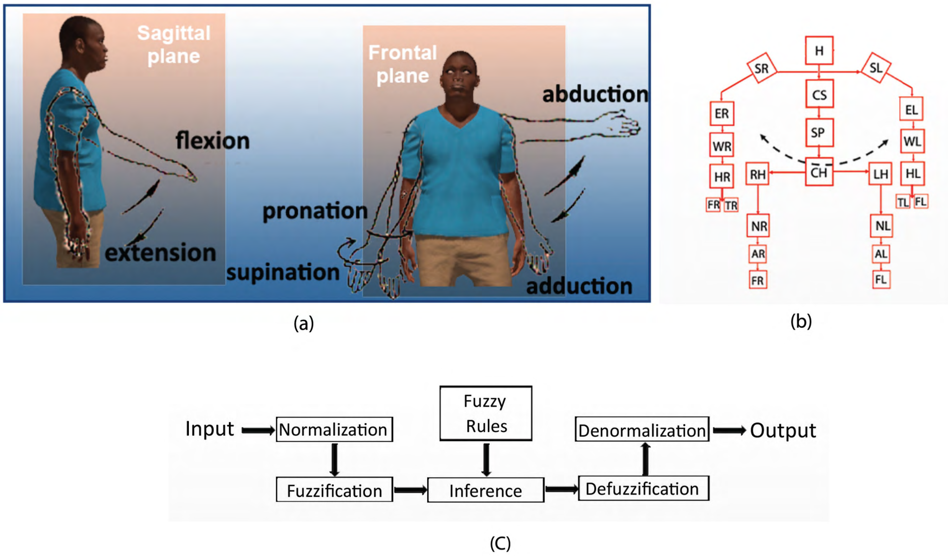

FIGURE 1. **(a) The reference planes for the anatomical motion to describe the axis along which an action is performed. (b) The stick figure and the skeleton joints tracked by the Kinect. (c) The schematic of fuzzy logic classification in the game.**

($g = 9.81m/s^2$), both static (gravity) and dynamic (sudden starts/stops) acceleration. By incorporating gyrometer the roll, pitch, yaw data determined. The acceleration calculated following subtracting the acceleration due to gravity, integrated once to obtain speeds and integrated twice to determine displacements along three axis. A gyroscope measured angular velocity in $°/sec$.

Saitek footPedal has 3-axes and is utilized for exploring the virtual world. The player guides the movement while they sit before the screen, toe push enables switching towards left or right. It is connected to the game via the USB connector and has an adaptable tension dial with a range of forces that are employed to set up reasonable resistance for fitting strength. The footrests adjust to accommodate a range of dimensions and incorporate non-slip rubbers to retain the device in place.

C. DATA COLLECTION

Kinect Data Upper body data are determined relative to the standard anatomical position, and lower body data are relative to the idle sitting position. The data includes; motion, velocity, time, displacements (vertical/horizontal) as well as kinematic parameters.

- The orientation (O) and position (P) of the wrist (O_W), (P_W), elbow (O_E), (P_E), and shoulder (O_S), (P_S) when the objects are spawned relative to the location (effector) and knees (O_N), (P_N).
- Average angular velocity (AV) of the wrist(AV_W), the elbow (AV_E), and the shoulder (AV_S) and knees (AV_N), (AV_N).
- The time an object is "spawned," "reached" and "collected."
- Head Tilt (T_H) and Hip Tilt (T_HP) are used to measure the body posture. The (T_HP) calculated relative to the position of left, right position of hip and its mean value.

1) MYO ARMBAND DATA

- 8-EMG (ElectroMyoGraphy) input information are assembled to estimate the electrical activity originated in lower arm muscles. These data are accumulated independently in vectors; EMG_i, $i \in \mathbb{Z}$, $i = [1, 8]$.
- The gyroscope, magnetometer and accelerometer data of the lower arm are known as inertial measurement unit and collected in a matrix; $IMU_i, i \in [X, Y, Z]$, to identify the roll, pitch and yaw orientation of player's arm throughout the experiences.

2) PEDAL DATA

- Forces applied on foot Pedals: It monitors the significance of force applied by each foot which varies within $i \in \mathbb{R}, i = [-1, 1]$ and determines (I) if the steps are executed in alternative orders, (II) measures the amount of pressure applied on each pedal; Left and right foot pressures are $P_{(LF)} = -1$ and $P_{(RF)} = +1$ respectively and neutral $P_{(N)} = 0$ which are registered per frame. The average value is presented as $P_{(Avg)}$. If the $P_{(Avg)} < 0$, the left foot is dominant, and if $P_{(Avg)} > 0$, the right foot is the dominant foot.

The hand gestures were validated with repetitive actions facilitated by the game with various trajectories. Fig. 2 illustrates the raw data collected from Myo with reach, grab, hold on, release tasks. Figure 2 (a) to (f) illustrates the data collected by the three-axis accelerometer and gyroscope. The idle, move the hand towards the target/virtual fruit, grab it,

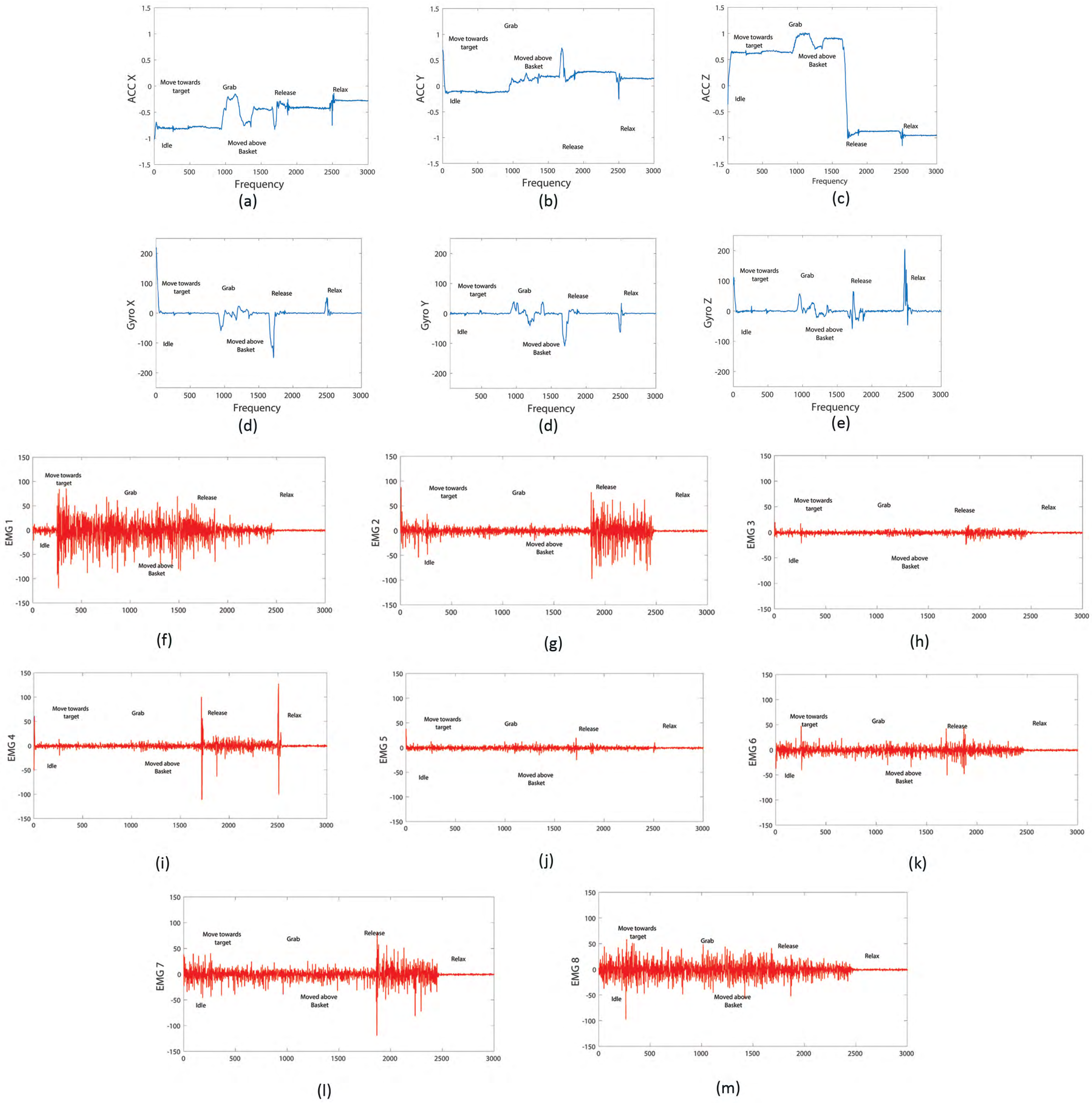

FIGURE 2. The Myo armband raw data collected while a control subject interacted with the game. The activities included; the player's hand is positioned next to the body (idle). The hand moves towards the target (virtual fruits), grab the object, moves above the virtual basket, brings the hand down, releases the virtual fruit and is back to idle. The acceleration is specified in (g), and the gyroscope readings are in (∘/*sec*).

move the hand above the basket to release the object, and finally relax the hand (idle) are segmented. Fig. 2 (f) to (m) shows the muscles contraction based on the EMG sensor's location on the arm. As it is visible, some muscles engagement in the activities were higher compared to the others.

A sixth-order Butter-worth band-pass filter with different cutoff frequencies was used to exclude noises. Savitzky-Golay filter was used to remove noise from the IMU data. The 50 Hz power line noise removed using 3 dB pass-band followed by wavelet method. EMG raw signals are transformed into a representation set of feature domain (feature extraction). The features were extracted for each type of hand movement from the denoised data - waveform length time-domain feature extraction method used to present the characteristics of signals for different arm movements due to its high rate of accuracy and stability to changes in segmentation method. The Myo was placed on a level table top while it was worn on the lower arm, and slide along a straight line for distances of half a meter. The noise was filtered by adjusting the initial and final velocities to zero followed by pose identification. Four hand gestures were segmented; each segment consisted of 500 data points taken from twelve control subjects. Each subject performed four hand gestures and an idle while each movement was held fixed for five seconds. The identified four gestures were; 1. Wave hand for reach or move to a target, 2. Fist for grasp or hold on to an object (to carry virtual objects from point A to B), 3. Release an object using stop hand sign (spread fingers) and 4. Idle or relaxed hand gesture.

D. INVERSE KINEMATICS (IK)

The kinematics of the human body is explicitly concerned with figuring and understanding for the interpretation, turn, position, and speed of each body section in movements [16]. The movement of a kinematic chain, regardless of whether it is a robot or an animated character, is modeled by the kinematic equations of the chain [17], [18]. The IK determined the common parameters that give an ideal position of the end-effector to finish an assignment (activity arranging) [19]. Implementing IK enabled us to have direct control over the trajectory of limbs based on the kinematic chain of joints, and the individual rotating joints within a skeleton [20]. As such, the system automatically computed the optimum joint angles based on the virtual object's location (effector).

E. FUZZY LOGIC (FL)

Fuzzy Logic incorporates human's logic and their reasoning strategy [6], [21]. There is a progressive transformation in the fuzzy set from one condition to another rather than sharp change with overlapping fuzzy interval changes. It mimics the process in that human perceives scientific reasoning. Reference [22] used a fuzzy logic inference system to estimate the instantaneous risk of fall through a holistic model. It predicts the risk of fall based on reliable inputs, results to a useful feedback mechanism as an outcome.

FL implements a structure for the classification of imprecise mandates via the use of obscure *if/then* or *or/and* commands. The important concepts in the statement of a fuzzy set are linguistic variables, membership functions (MF), and the discourse universe [23]. A fuzzy system is a combination of real numbers having membership in the set where a membership value conditions the total number of fragments in the set; absolute exclusion is 0, and partial membership in the set is between [0, 1] [24]. An MF curve defines how a particular feature in the input space is outlined to a membership value [0, 1]. The membership function obtains the standard scale for inputs [25], [26]; the (MF) specifies a fuzzy set A in X, specifies by the function $(x, \mu_A(x))$, and mathematically arranged via; $A = \{(x, \mu_A(x)) \mid x \in X\}$.

In this study, FL was applied to investigate the data based on the universe of discourse to consolidate imprecise data into a decision-making rule. The collection of numbers on which a variable is defined are the universe of discourse for the variable. The FL logic adaptation scheme obtains a decision based on the player's achievement and consequently suggests a suitable level of adjustment combination relevant for the rehabilitation purpose.

F. FUZZY LOGIC CONTROLLER

Two main tasks are required to design an intelligent FL system; fuzzy operators and adequate knowledge. Selection of the fuzzy operators that are involved in the inference system, and driving adequate knowledge about the problem being solved [27], [28]. The MF of the fuzzy system is triangular in the range of [0, 1], which is explained in [6] in more detail.

We developed a multi-input and single-output (MISO) fuzzy system which is designed based on inputs, a set of fuzzy input specifies fuzzy if-then rule, a fuzzy output set and a set of parameters [26]. The schematic of the fuzzy system is illustrated in Fig. 1 (c). The defuzzification interface is required to achieve output in that the contribution of each fuzzy collection inferred analyzed independently employing a characteristic value and center of gravity; the final crisp value is acquired through a weighted average aggregation operator [29], [30].

$$U = \frac{\int_{min}^{max} u\mu(u)du}{\int_{min}^{max} \mu(u)du}$$

where U is the result of defuzzification, u is the output variable, μ membership function after accumulation, min shows the lower limit of the defizifier and max is the upper limit. The intelligent fuzzy logic inference scheme suggests an application that is more appropriate for the player based on their achievement without any additional injury. The uniformity ingredient of the training was adopted on input parameters that render a quantified value that expresses how well a patient administered in a demanding task. Input quantities are normalized and assigned for fuzzification through fuzzy collections, a set of predefined precepts are applied to fuzzy sets by the fuzzy inference that leads them through defuzzification and denormalization level to the stimulating output μ. Below is the list of steps towards producing the fuzzy logic operation: **Input and output variables:** The data variables depend on the subjective evaluation and the severity of the limitations associated with the game. A maximum of thirteen fuzzy variables is recognized depending on the various distinct tasks and the detentions. It possibly generates an output which directs the player towards "Progression", Repetition," "Simplification" or "Harmfulness" stage. This data can be actuated or deactivated through the interface by clinicians or players before attempting the game depending on the required confinements. Four subsets are assigned to the input variables position, orientation and average angular velocity as follows: "Very Good (VG), Good(G), Bad (B), and Harmful (H)", and the time has three subsets (VG, G and B)," demonstrated in Fig. 3. Some fuzzy logic input functions are outlined below along with the yield function.

- $O.E_W$, $(P.E_W)$, $O.E_E$, $(P.E_E)$ **and** $O.E_S$ $(P.E_S)$**: The Orientation (and Position) variation (error) of the Wrist, Elbow and Shoulder**, portrayed as the disparity between the player controlled avatar joints orientation (and position) against virtual mechanical avatar. The orientation subsets errors vary in the range of [0°, 90°] where (0° ⇔"VG") and (90° ⇔"H"), and for position (0 ⇔"VG") and (90 ⇔"H").
- $AV.E_W$, $AV.E_E$, **and** $AV.E_S$**: The Average Angular Velocity Error of the Wrist, Elbow, and Shoulder**. Described as the discrimination between the joints normal precise between the average angular velocities. The component of a universe of discourse is in the scope of [0, 90] where (0 ⇔"VG") and (90 ⇔"H").

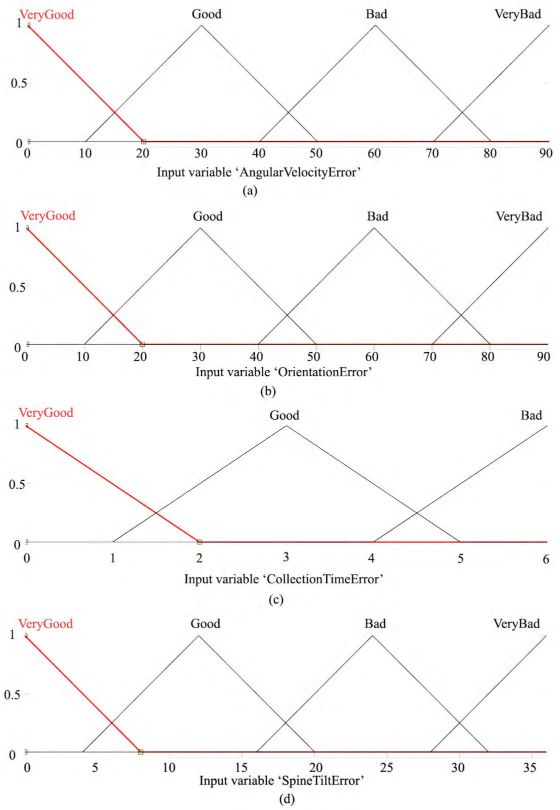

FIGURE 3. The fuzzy logic input variables.

- $T.E_H$ **and** $T.E_{HP}$**: The Head and hip Tilt Error**. These parameters screen the player's standing pose (the body posture) in that the hip tilt error $T.E_HP$ is in the scope of $[0°, 36°]$ deg in that (36° ⇔"H"). The head inclination is in the scope of $[0°, 32°]$ toward every direction (0° ⇔"VG") and (32° ⇔"H").
- $T.E_C$ **and** $T.E_R$**: The Collection and Release Time Error**, defined as the difference between the collection and release time. These two variables are in the range of $[0, 6]$ where (0 ⇔"VG") and (6 ⇔"B").
- **Output parameter (GameProgress):** has four-subset extending in $[0, 80]$. Where $[0-20] \subseteq$ Progression, $[20-40] \subseteq$ Repetition, $[40-60] \subseteq$ Simplification and $[60-80] \subseteq$ Harmfulness.

The triangular fuzzy assemblage forms are arranged inside the limitations of the above circumstances with little arbitrary error overlays (Fig. 3). This advances a conventional system for a fuzzy set representation of a new system and simplifies the calculations and furthermore reduces the demand for computer resources.

1) LINGUISTIC RULES AND CONSTRAINTS

The control rules are performed utilizing fuzzy conditional observations (if/then, or/and, not) and the associations between subsets. $A \times B$ (maximum/or), $A+B$ (minimum/and) and ΓA (negation/not). The rules are derived from the test discoveries, physiotherapy consultancy and coordinated, driving joint speculation (elucidation of control of human movements) and information suggesting relations between the angle of joints [27] and defined by Eqn. 1.

$$\begin{aligned}
&IF\ P.E_W\ is\ \ldots\ AND/OR\ P.E_E\ is \ldots\ THEN\\
&\qquad P.E_S\ is\ \ldots\\
&IF\ O.E_W\ is \ldots\ AND/OR\ O.E_E\ is \ldots\ THEN\\
&\qquad O.E_S\ is\ \ldots\\
&IF\ AV.E_W\ is \ldots\ AND/OR\ AV.E_E\ is \ldots\ THEN\\
&\qquad AV.E_S\ is\ \ldots\\
&IF\ T.E_H\ is \ldots\ AND/OR\ T.E_S\ is \ldots\ THEN\ \ldots\\
&IF\ T.E_C\ is \ldots\ AND/OR\ T.E_R\ is \ldots\ THEN\ \ldots
\end{aligned} \tag{1}$$

G. NEURAL NETWORK CLASSIFICATION ALGORITHM

The feed-forward back-propagation neural network is a curve fitting arrangement calculation in that units are associated dependent on their qualities or weights. The weights on the connections encode the knowledge of a network. Feed-forward neural networks (FFNN) often have one or more hidden layers of sigmoid neurons pursued by a yield layer of direct neurons. Numerous layers of neurons with a nonlinear exchange function was incorporated to enable the network to learn nonlinear relationships between the input and output data. In FFNN there is no feedback between the network's layers. Multilayer networks were prepared to generalize well within the range of inputs for which they have been trained and cannot extrapolate beyond this range, so it is essential that the preparation information length the full scope of the information space.

The non-linear autoregressive neural network (NAR) was additionally led to surmised the capacity utilizing the advancement of the system weights and neuron inclination through Levenberg-Marquardt backpropagation (LMBP). This training function is the fastest back propagation-type algorithm.

The error on the approval set is observed amid the preparation procedure. The approval blunder diminishes regularly amid the underlying period of preparing, as does the training set error. In any case, when the system starts to over-fit the information, the blunder on the approval set commonly starts to rise. The network weights and biases are spared at the base of the approval set blunder.

The generalization regularization was used which includes altering the execution function, which is generally picked to be the sum of squares of the network errors on the preparation set. Network's capacity to generalize empowers the network to stops its training to maintain a strategic distance from over-fitting. Over-fitting occurs when a network has remembered the preparation set however has not figured out how, to sum up to new sources of info which causes a moderately little blunder on the preparation set yet a lot bigger error when new information is presented to the network.

TABLE 1. Demographic characteristics of participants.

Variables	Results
Age	60.1 (11.02)*
Male vs Female	26 (%65.0) vs 14 (%35.0)
Time since the outset of MS symptoms(months)	59.9 (14.8)*
Subjects for Right upper-limb rehabilitation	Sum=17, 0.425 (0.406)*
MAS: Hypotonus (low muscle tone)	3 (2.3)*

*Mean (SD)

IV. RESULTS AND DATA ANALYSIS

A. SUBJECTS

Forty casualties with MS and twelve healthy subjects volunteered to participate in the study. The patients had a diagnosis of relapsing-remitting MS, secondary progressive MS (47%) and primary progressive MS (53%). The institution certified ethics approval and consent form were provided and signed by participants in advance. The healthy subjects were recruited as the control group, to identify the poses as well as to train the NN. Twenty-six male and fourteen MS female casualties had the mean age and standard deviation of (60.1 ± 11.02). The collected data were averaged over hundred and twenty readings. Table 1 summarizes the demographic and clinical characteristics of the MS participants at the time of admission. Therapy sessions were performed one hour, five days a week for ten weeks. Two therapists supervised and scored participant's motor assessment scale (MAS), [31], pre- and post-rehabilitation. Participants performed each tasks three time, only the best performance was recorded. Rehabilitation sessions were performed for one hour, five days a week for ten weeks.

B. DATA ANALYSIS

All raters demonstrated clinically acceptable (high and significant) inter-rater reliability $r = 0.89$ coefficients for the use of the scale and individual items. The significant finding evident from the MAS data was that for each item most patients improved, and no one reverted. For each item of the MAS the mean difference was determined for the scores pre- and post-rehabilitation. Paired samples t-test was performed using SPSS Statistics 24. The test made statistically significant difference, P-value < 0.001, mean $t = -12.82$, mean standard error $MSE = 0.13$ and mean intervals $[-1.89, -1.36]$. The degree of freedom was $df = 39$ data and significant values showed that the rehabilitation was effective. Table 2 outlines the means ($\bar{X}$) and standard deviation SD of each item collected from forty MS casualties pre- and post-rehabilitation. MAS $point = 0$ indicated the min range of movement (ROM) and $point = 6$ is the maximum.

The Neural Network Toolbox in MATLAB was used along Unity game engine. The data were transferred into MATLAB for analysis. The NN analysis was performed based on data self-organizing map (SOM), non-linear autoregressive (NAR) and pattern-recognition with the two-layer feed-forward network to develop an optimal classifier.

TABLE 2. Average MAS scores for each items in the appendix pre- and post-rehabilitation.

Motor Assessment Scale	Item	Pre-treatment		Post-treatment	
		X	SD	X	SD
Upper Arm Function					
	1	2.08	0.94	3.98	1.03
	2	2.45	0.90	4.20	0.76
	3	2.25	0.87	4.13	0.88
	4	2.43	0.87	4.25	0.71
	5	2.33	0.76	4.38	0.63
	6	2.00	0.68	3.53	0.51
Hand Movements					
	1	2.03	0.70	3.55	0.64
	2	2.48	0.85	3.70	0.76
	3	3.03	0.62	4.43	0.59
	4	2.60	0.84	4.40	0.74
	5	1.95	0.68	4.15	0.66
	6	2.60	0.93	4.15	0.70
Advanced Hand Activities					
	1	1.48	0.85	2.60	0.74
	2	1.45	0.88	2.88	0.69
	3	1.75	1.03	3.00	0.99
	4	1.80	1.11	3.03	1.00
	5	1.88	1.16	3.55	0.93
	6	1.33	0.69	3.25	0.67

The input p in MATLAB was multiplied by the weight w and was fed to the summing junction wp. The neuron has a bias b, which is summed with the weighted inputs to form the net input n. The net input is the argument of the differentiable alteration function Log-Sigmoid $= f$, which is applied in the hidden layers of multilayer back-propagation interface. f was united for pattern recognition problems that take the input $[-\infty, +\infty]$, to generate output and squeezes it into the range of $[0, 1]$.

C. ARTIFICIAL NEURAL NETWORK (ANN)

We integrated Artificial Neural Networks (ANNs) which are mathematical models of the biological brain to detect complex non-linear correlations among the data [32]. Clustering in NN was utilized to train the network based on inputs patterns. The network learns from data and comes up with designs according to the similarity and applicable topology. The supervised neural networks were trained to produce desired outputs in response to the inputs. The inputs were arranged into a matrix of ten vectors to build the NN. The task completion timing, shoulder, and elbow joint roll, pitch, yaw data, hand poses, MAS scores and averaged EMGs. The NN algorithm learned from the upper-limbs data through the supervised network which was facilitated by 70% of collected data pre- and post-rehabilitation and corresponding MAS scores and improvements. It was learned from the patterns generated which were followed by network validation using the 15% of data. The results of the NN are presented in Table 4 and Table 3 for FFNN and NAR LMBP, respectively. The success rate of the classification and its prediction was increased by 4.32% using NAR LMBP compared to FFNN. The other 15% of data was implemented as a completely independent test of the network with the success rate of 93.3% using LMBP compared to FFNN which was 89.2%.

TABLE 3. Feed-forward neural networks (FFNN).

Results	Samples	CE	%E	Validation	MSE	R
Training	2560	0.84	3.27	92.4	0.005	0.89
Validation	549	1.12	5.34	90.3	0.008	0.84
Testing	549	1.09	6.35	89.2	0.003	0.81

TABLE 4. Non-linear autoregressive neural network with Levenberg-Marquardt backpropagation (LMBP) optimization.

Results	Samples	CE	%E	Validation	MSE	R
Training	2560	0.44	0.86	96.1	0.0003	0.99
Validation	549	0.90	0.82	94.2	0.0002	0.99
Testing	549	0.89	0.73	93.3	0.0001	1

D. RESULTS

The training of the ANN was performed and continued until it reached the lowest level of mean squared error (MSE) at epoch 102, with the best performance validation at the gradient of ≈ 0.025 as illustrated in Fig 4. The typical performance function used for training feed-forward neural networks is the mean sum of squares of the network errors. Minimizing Cross-Entropy (CE) results in good classification, zero means no error Fig 5. Percent error ($\%E$) indicates the fraction of samples which are misclassified where 0 indicates minimum misclassifications. The number of hidden neurons was adjusted based on the values of CE and $\%E$ as shown in the Table 4. The mean squared error (MSE) or the average squared difference, as well as regression R value which is the correlation between outputs and targets, show small error and close relationship between data. The MSE and R are close to zero and one, respectively for NAR which shows a better classifier.

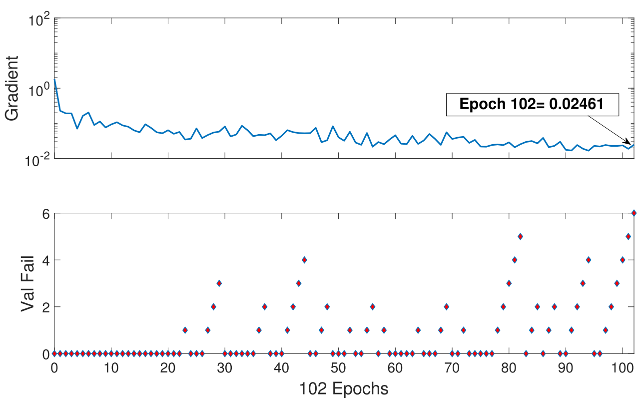

FIGURE 4. Epoch 102 and the gradient. The scale conjugate gradient used for training the data in NN pattern recognition with 100 epochs. The epochs value used for data validation which is in the range of [0,6].

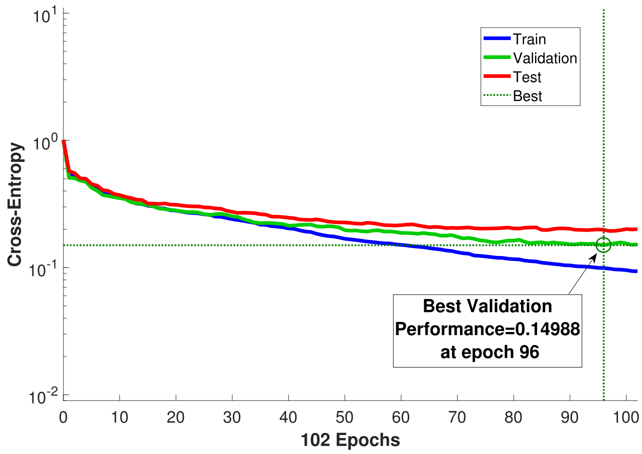

FIGURE 5. Crossentropy. Neural Network training performance. The training stopped once the MSE (mean square error) for validation data reached its minimum value (at epoch 96).

The clustering algorithm grouped the data by their similarity. The Self-organizing map (SOM) batch algorithm arranged neurons of size 10 × 10 (a 2D map) into weight plane for each element of the input vector as shown in Fig. 6. It trained the network to learn the topology and distribution of the input samples. The darker colors represent larger distances, and the lighter colors represent smaller distances. The grouping indicates that the network has clustered the data into various groups. The weights connect each input of the neurons into lighter and darker colors which represent larger and smaller weights, respectively. If the connection patterns of the inputs are very similar, it means that the inputs are highly correlated. The input three and four are similar, and inputs seven, eight, and nine are similar as well. The input weights of one, two, five, six and ten are very different illustrated in Fig. 6.

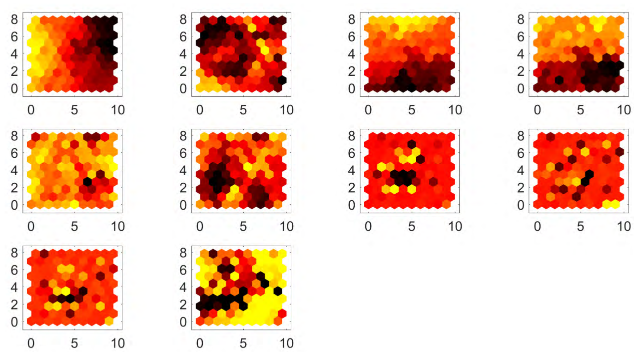

FIGURE 6. Weights from Input 1 to 10. SOM planes for inputs one to ten. The visualizations of the weights that connect each input to each of the neurons.

V. DISCUSSION AND CONCLUSION

VI. DISCUSSION

Upper body Range Of Movement (ROM) and gait classification are general methods for exploring pattern recognition. This study, integrated the signals from IMU, EMG, foot Pedal, joint orientation, MAS score, and repetitive encoding activities to develop a new algorithm for identifying ROM post-rehabilitation and recognizing the transition between motion patterns. Our algorithm analyses complex vigorous activities of motor-impaired individuals that are an essential factor to help an individual to function well in daily tasks.

Walking is the periodic behavior of one stride, measured from one leg's heel strike (ground contact) to the same leg's next heel strike. One stride can be further divided into two phases, the stance in which one leg bears the weight of the body and the swing whereby the leg moves forward to propel the body [33]. The swing starts when one foot leaves the ground (toe Off), ends when that foot next contacts the ground (heel-strike). The stance occurs between the heel-strike and the toe off. We incorporated stance in our settings which was integrated into the video game and leveraged via the foot Pedal. It determines if the steps are taken in order and measured the amount of pressure applied by each foot from which the pattern recognition was developed. The joints orientation, lower arm, and foot Pedal data were first acquired from twelve control subjects (non-disabled volunteers). The experimental data were aggregated using control subjects, and MS casualties and executed at ten-millisecond intervals. The threshold was determined heuristically from several trials and data were pre-processed to transform them into available information for classification. The training and validation were conducted on raw data where the diverse data points from various devices were combined into a single point and synchronized with the pre-rehabilitation MAS score for each. The synchronization with signals was performed in MATLAB. The data were cut into several shorter series to demonstrate the particular gesture and gathered the data into the data set.

The classification method employed in this study is a regulated learning algorithm in which the preparation and approval sets are made out of sets of information and desired yield. The inputs utilized for the training and validation of our classifier. The angular velocities of the upper body are calculated by differentiating the joint angles at five-millisecond intervals. NN could be antagonistically influenced by the components of the info matrices with a wide range of qualities; therefore, a type of standardization was performed to maintain a strategic distance from this issue. We embraced cross-entropy activation functions in the output layer of pattern recognition and classification. It is realized that the capacity of a NN to model complex behavior increases with the number of hidden layers. Nonetheless, too many concealed layers can prompt issues, for example, over-fitting and unnecessary preparing times. The number of nodes in the hidden layers must also be considered carefully. Too few nodes in the hidden layers can limit the network's ability to reproduce the target function's behavior, whereas too many can result in over-fitting. We used a Self-organizing map and non-linear Auto-regression examination using Feed-Forward and Levenberg-Marquardt backpropagation. The sensors fault-tolerant module (SFTM) [34] was embraced to defeat the constraint of information signals/data. Any anomalous readings were expelled from the feature vector for classification to guarantee dependable framework execution. Finally, the element vectors were encouraged into the MATLAB NN classifier.

The framework offers the likelihood to give a customized, self-governing learned rehabilitation program for patients with neuromuscular disorders by performing various assistance developments. The rehabilitation game is an achievable and safe framework that could be used to enhance upper extremity limb function in patients with motor impairment. This framework is created to assist patients with improving motor confinements and motivate physical rehabilitation. The outcomes propose that low-cost home-based devices (Kinect, Myo, and footPedal) can precisely gauge the planning of development redundancy, measure the timing of movement repetition, Kinematic activity, and ROM. The statistical analysis has shown a significant improvement in participant performance post-rehabilitation which was reflected in response times and range of motion. All participants with motor impairment showed high interest and engagement during the activities. The players exhibited the positive inclination and improved moods while playing the game and the delight of checking high score accomplishment additionally kept the members locked in.

VII. CONCLUSION

The players guided the avatar in the ''Fruit-Collection and avatar manoeuvring'' video game in that the movements are managed and conveyed via the Kinect and foot Pedal in real-time. The players interacted with virtual fruits by showing the hand palm to the Kinect device followed by spread fingers and fist gesture to grab or release objects. The foot Pedal algorithm determined if the steps are taken in order; otherwise, the forward movement did not occur. The left/right feet push took the avatar forward, and toe presses enable turn left or right. The body's joint orientation, angular velocity, hand gestures, object's spawn location, collection and release timing, lower arm's IMU and EMG data, foot Pedal data are all collected in real-time and used for NN analysis. Hand gestures validated with repetitive actions which were facilitated by the game with various trajectories. The idle, move the hand towards the target/virtual fruit, grab it, move the hand above the basket to release the object, and finally idle were segmented. Butter-worth band-pass filter with various cutoff frequencies was used to remove noise from the signals. The kinematic equations of the chain modeled the movement via IK and used to determine the optimum orientation based on the end-effector. FL provided a framework for the description of imprecise dependencies through the use of fuzzy rules. The FL logic adaptation system made a decision based on the player's performance and accordingly recommends an appropriate level of orientation combination appropriate for the rehabilitation purpose. Multi-input and single output fuzzy system were generated, and the defuzzification interface adopted to achieve crisp outputs. The normality factor of the training was procured on info parameters to give evaluated esteem that portrays how well a patient performed in a specific undertaking. Thirteen fuzzy factors are perceived relying upon every particular undertaking with the limitations to create a yield which coordinates the player towards ''Progression'', Repetition, ''Simplification'' or ''Harmfulness.'' Triangular fuzzy outlines were planned with little subjective error overlaps.

Artificial Neural Networks mathematical algorithms were used to detect complex non-linear correlations among data collected from fifty-two participants. Clustering in NN arranged the data according to the pattern similarity and relevant topology. LMBO supervised neural network produced optimized outputs in support of the inputs. The successful classification rates were around 94.34% which means the algorithm could successfully predict future events. 70% of the collected data were utilized for training the system, 15% for validation and the other 15% was applied as a completely independent test of network generalization. The results showed that the inter-rater reliability was high enough. Furthermore, the MAS scores improved comparing the mean difference of the pre- and post-rehabilitation via paired samples t-test. This study confirmed the effectiveness of neural networks in predicting the improvements following the rehabilitation program with positive impacts on the medical society and the Multiple sclerosis (MS) immune system problem. The future work will look at using the data-set to achieve a dynamical coupling between a player and a prosthetic arm/artificial limb.

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